When do the USDA forecasters make mistakes?

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"The U.S. Department of Agriculture's failure to accurately predict the size of the current corn-crop harvest has undermined confidence of some investors in the agency's forecasting, which has for years been held as gospel."

(Wall Street Journal, October 22, 2010)

The U.S. Department of Agriculture (USDA) "…is widely considered unmatched in its data gathering resources… The National Agricultural Statistics Service, part of the USDA, has a $156.8m budget for approximately 500 reports each year and 1,050 employees." (Meyer, 2011) Due to the unmatched resources used and the generally high quality of information provided, USDA forecasts function as the "benchmark" to which other private and public forecasts are compared. The dominant role of USDA forecasts is not surprising given the classic public goods problem of private underinvestment in information and the critical role that public information plays in coordinating the beliefs of market participants. The data collection and forecasting role of the USDA is particularly important in an environment where G-20 countries are developing an agricultural market information system (AMIS) in response to recent food price volatility. This system will improve access to data on production and stocks of most food commodities (Boschat and Moffett, 2011).

It has been widely documented that the release of many USDA reports moves the markets. For example, Isengildina-Massa et. al. (2008) showed that volatility in corn and soybean futures markets increases about 7 times on report release days. The release of the reports is usually widely watched by traders and other market participants. The market impact of the reports implies that the errors in USDA forecasts may have large consequences. A Financial Times article (Meyer, 2011) notes that "the importance of the estimates was highlighted last week, when, according to Reuters, a senior official at Cofco, China's state grain trader, called

USDA data an ‘insult’ that threatened ‘huge losses to our enterprises.” In addition to market effects, errors in USDA price estimates may lead to large changes in payments to producers, since some government payments are calculated based on these estimates.

Evaluation of USDA forecasts in the previous literature has largely focused on production and price forecasts. For example, Bailey and Brorsen (1998) demonstrated that USDA forecasts underestimated beef and pork production in the 1980s, but the bias has disappeared since then and the variance of the forecasts has also declined. Sanders and Manfredo (2002) found that USDA forecasts of pork, beef and broiler production were unbiased but not efficient with respect to past forecasts and they did not encompass all the information contained in simple time-series models. Isengildina, Irwin, and Good (2006) argued that revisions to USDA corn and soybean production forecasts were “smoothed,” meaning that not all information available at the time the forecasts were made was incorporated in the forecasts and some was carried into the next forecast, which could cause substantial loss in accuracy. Sanders and Manfredo (2003) investigated one-quarter ahead forecasts of quarterly live cattle, live hog and broiler prices and found that broiler price forecasts were biased and all forecast series had a tendency to repeat errors. While USDA correctly identified the direction of price change in at least 70% of its forecasts, only 48% of actual prices fell inside a forecasted range for broilers and 35% for hogs. Isengildina, Irwin, and Good (2004) found that corn price forecast intervals contained the actual prices 36% - 82% of the time, while soybean intervals did so 59% - 86% of the time.

The goal of this study is to analyze USDA forecast errors in an attempt to identify patterns and better understand when the USDA forecasters make mistakes. We hypothesize that errors in USDA forecasts may stem from three general sources. The first one deals with forecasters' abilities and reflects behavioral characteristics and tendencies as described by Kahneman and Tversky (1973). Thus, forecasting behavior may be different with respect to predicting positive vs. negative change and extreme vs. moderate rate of change (Denrell and Fang, 2010). The second source reflects data that are not (efficiently) included in the forecasts. Previous studies (Sanders and Manfredo, 2002, 2003) showed that USDA forecasts do not encompass simple time-series models. In our study we investigate whether USDA forecasts fail to efficiently take into account macroeconomic data and tend to show mistakes during certain economic conditions, which has not been analyzed in previous studies of these forecasts. The third source of forecasting errors may stem from the data forecasters use. Most fundamental models of commodity prices rely on uncertain estimates of independent variables, and errors in those variables may cause errors in price and ending stocks forecasts.

This study focuses on forecasts for all U.S. corn, soybeans and wheat categories published within the WASDE (*World Agricultural Supply and Demand Estimates*) reports over the 1987/88 through 2009/10 marketing years. These forecasts are of particular interest because corn, soybeans and wheat account for over 90% of total U.S. grain and oilseed production. While some characteristics of corn and soybean production and price forecasts have been examined before (Isengildina, Irwin and Good, 2004, 2006), the accuracy of most other USDA forecasts describing supply and demand forces has been largely overlooked. To the best of our knowledge, only a few previous studies analyzed a broad range of WASDE production and consumption forecasts for corn and soybeans (Botto et.al., 2006), cotton (Isengildina, MacDonald and Xie, 2012), and sugar (Lewis and Manfredo, 2012). Knowledge of supply and demand forecasts accuracy is important because these categories serve as building blocks for price forecasts. Furthermore, supply and demand estimates are published within a set of other forecasts in WASDE reports that have been shown to affect the markets.

WASDE Forecasts

WASDE reports are typically released by the USDA between the 9th and the 12th of each month and contain forecasts of supply and demand for most major crops. WASDE forecasts follow a balance sheet approach, accounting for each component of supply and utilization (see Vogel and Bange (1999) for a detailed description of the USDA crop forecast generation process). The supply side of the balance sheet consists of beginning stocks, production, and imports. Utilization includes domestic use (or consumption), exports, and ending stocks. The ending stocks for year *t* become beginning stocks for year *t*+1. The balance sheet approach requires that "total supply must equal domestic use plus exports and ending stocks. Prices tie both sides of the balance sheet together by rationing available supplies between competing uses" (Vogel and Bange, p. 10). Unlike all other estimates, price forecasts are published in interval form. Because different procedures should be used for interval forecast evaluation, midpoints of the published intervals were considered in this study to keep analysis consistent across all categories.

Several agencies within USDA are involved in preparing these forecasts: National Agricultural Statistics Service (NASS) collects data on U.S. crop production and stocks; Farm Service Agency (FSA) describes current policy environment and farmers' reaction to current policies; Agricultural Marketing Service (AMS) provides current price and marketing reports; Foreign Agriculture Service (FAS) provides information regarding foreign production, use and trade; Economic Research Service (ERS) identifies important economic effects and implications for prices, quantities supplied and demanded; World Agricultural Outlook Board (WAOB), with separate leaders for each commodity, coordinates the interagency process used to produce WASDE estimates. This process ensures that the best available data is used and the estimates are consistent across all USDA publications.

All estimates are forecasted on a marketing year basis (September through August for corn and soybeans and June through May for wheat), thus forecasted values represent marketing year averages. Figure 1 demonstrates marketing years and forecast months for the three commodities studied. The first forecast for a marketing year is released in May preceding the U.S. marketing year. Production and beginning stocks forecasts are generally finalized by October (for wheat) and January (for corn and soybeans) of the marketing year. All other estimates are typically finalized by next September (for wheat) and November (for corn and soybeans). Thus, there is a 9 (6) month forecasting cycle for production and beginning stocks forecasts, and 19 (17) month for all other categories for corn and soybeans (wheat).

Within this forecasting cycle, forecasts differ dramatically with respect to the amount of available information. For corn and soybeans, May-August forecasts are provided during the growing season and reflect new information about the development of the crop. September-November forecasts represent harvest-time forecasts and production uncertainty is limited to the challenges of the harvesting process. December-August forecasts generally are considered post-harvest with uncertainty driven mainly by the speed of consumption. Post-August estimates reflect revisions of the observed marketing year data. USDA wheat forecasts combine information for both winter wheat and spring wheat. For winter wheat, the growing season is May, the harvest season is June-July, and August-May is the post-harvest season. For spring wheat, the growing season is May-July, the harvest season is August-September, and October-May is a post-harvest season. Combining this information, the forecasts may be largely differentiated into highly uncertain stage 1 forecasts during May-August (May-June), less uncertain stage 2 forecasts during September-November (July-August), stage 3 forecasts during December-August (September-May) and stage 4 estimates during September-November (June-September) for corn and soybeans (wheat).

USDA's WASDE forecasts are considered fixed-event forecasts because the series of forecasts is related to the same terminal event (y_t^J), where J is the release month of the final estimate for marketing year t. The forecasted value published in month j of marketing year t is denoted as y_t^j, where j = 1, . . . , J, and J = 19 for corn and soybeans and J = 17 for wheat. Thus, each subsequent forecast is an update of the previous forecast describing the same terminal event. The terminal event for each category describes a marketing year total (for production, consumption, and stocks categories) or average (for price) values. Based on our definition of a 19 (17) month forecasting cycle, WASDE generates 18 (16) updates for each U.S. variable forecasted except production and beginning stocks[2] (8 updates for corn and soybeans and 5 updates for wheat) within each marketing year. The marketing years covered in this study are t = 1(1987/88), …, T (2009/10), and T = 23.

To avoid the impacts of changing forecast levels over the study period on forecast evaluation and analysis, forecasts f_t^j were defined as percent changes in forecasted values from the previous year's values:

(1) $f_t^j = 100 * ln\left(\frac{y_t^j}{y_{t-1}^{j+12}}\right)$, $t = 1, \ldots, 23;$ $j = 1, \ldots, 6$ for corn and soybeans; $j = 1, \ldots, 4$ for wheat,

(2) $f_t^j = 100 * ln\left(\frac{y_t^j}{y_{t-1}^J}\right)$, $t = 1, \ldots, 23;$ $j = 7, \ldots, J$ for corn and soybeans; $j = 5, \ldots, J$ for wheat.

[2] Since beginning stocks category is the same as previous year's endings stocks, it is not evaluated as a separate category in this study.

Note that the denominator in equation (1) is labeled $j+12$ rather than J since, for USDA's year t forecasts during $j < 7$ for corn and soybeans and $j < 5$ for wheat, y_{t-1}^{J} is not yet known because the previous forecasting cycle is not finished by the time the new forecasting cycle started. For example, corn and soybean forecasts for j =13, …, 19, (j = 13, …, 17 for wheat) for marketing year t-1 and for j = 1, …, 7 (j = 1, …, 5 for wheat) for marketing year t are released in the same report. Thus, a first forecast for 2010/11 marketing year would be calculated as a percent change from the 13th forecast for 2009/10 marketing year (released in the same report), since the final value will not become known for a few months.

Since forecasts are measured in this study as percent changes from the previous year to control for scale, percentage forecast error e_t^j is calculated as[3]:

(3) $$e_t^j = f_t^J - f_t^j \qquad j = 1,..., J-1;\ t = 1,...,23.$$

The absolute value of this measure reflects the magnitude of the forecast error and its average describes forecast bias.

The means and standard deviations of the final forecast levels (y_t^J) shown in table 1 demonstrate the average magnitude and variability of the forecasted supply and demand categories. Since most of the analysis in this paper is conducted using percent changes in variables and percent errors, unit levels are presented here as a reference point for the relative size of the various categories. The coefficient of variation (CV) for food, seed, and industrial (FSI hereafter) likely reflects sharp changes associated with the use of corn for ethanol production, driven both by policy changes and the price of gasoline. Feed and residual use in

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[3] In this notation e_t^i is identical to traditional percent forecast error when the previous year's values are finalized:

$$e_t^j = f_t^J - f_t^j = 100 * \ln\left(\frac{y_t^J}{y_{t-1}^J}\right) - 100 * \ln\left(\frac{y_t^j}{y_{t-1}^J}\right) = 100 * \ln\left(y_t^J\right) - 100 * \ln\left(y_t^j\right) = 100 * \ln\left(\frac{y_t^J}{y_t^j}\right)$$

wheat is also a very variable category: since wheat is relatively expensive, its use for feed is residual to that of corn, thus making it a relatively small and highly variable category. Across all commodities, ending stocks is another highly variable category. Given the balance sheet nature of WASDE forecasts, ending stocks reflect the difference between all supply and demand categories, which means that forecast errors in other categories would be carried over to ending stocks errors. Descriptive statistics for percent forecast changes (f_t^J) provide another indication of relative volatility in forecasted categories, highlighting variability in year-to-year changes in all ending stocks and wheat feed and residual forecasts. Unlike the above statistics that focused on the final values ($j = 19$), error statistics shown in the last three columns of table 1 are calculated for the first 18 forecasts ($j = 1, \dots, 18$). Mean absolute percent errors (MAPE) and mean percent errors (MPE) describe the dependent variables used in the remainder of the analysis. MAPE illustrate the relative magnitude of forecast errors, reflecting large errors for highly variable categories described above: all ending stocks, soybean seed and residual and wheat feed and residual forecasts. MPE illustrate the presence of bias in the forecasts. Significant underestimation was detected in corn price, soybean crushings and price, and wheat exports and price, while overestimation was present in soybean seed and residual and ending stocks forecasts and wheat seed and feed and residual forecasts. The remainder of the manuscript examines the factors that affect both the size (APE) and the bias (PE) in the errors of these WASDE forecasts.

Sources of Error

In this study we hypothesize that errors in USDA forecasts stem from three general sources. The first source of errors deals with forecasters' characteristics. Previous studies suggest that forecasting behavior may be different with respect to predicting positive vs. negative changes (Dreman and Berry, 1995; Ashiya, 2003) and extreme vs. moderate rate of changes (Denrell and Fang, 2010). Amir and Ganzach (1998) argue that leniency, representativeness, and anchoring are the main reasons for forecaster's bias. Leniency describes a tendency for over-optimistic predictions, resulting in overestimating positive and underestimating negative changes as found in earnings forecasts (e.g., Givoly and Lakonishok, 1984; Schipper, 1991; Amir and Ganzach, 1998). Amir and Ganzach suggest that one of the possible reasons for leniency in earnings forecasts is the analysts' desire "to maintain good relations with management as a primary source of information." In the context of public commodity forecasts, however, this argument does not hold as the information contained in these forecasts has more "two-sided" effect: producers wait for the forecasts that increase prices, while users do just the opposite. Thus, an asymmetric reaction to positive vs. negative change in WASDE forecasts would likely be due to mis-calibration of forecasters' reaction to information and can result in optimism as well as pessimism. Given the public nature of the forecasts and their ability to affect markets, these biases should be unintended.

The representativeness heuristic leads to overreaction, causing forecasters to overpredict change (both positive and negative). Furthermore, Kahneman and Tversky (1973) argue that when using this heuristic, people choose a prediction value whose extremity matches the extremity of the predictive information, i.e. larger overestimation is associated with extreme vs. moderate rate of change, as observed by Denrell and Fang (2010). Contrary to representativeness, the anchoring heuristic results in underreaction. This heuristic explains situations when forecasters anchor their predictions at certain value and adjust them based on additional information. Since adjustment is typically insufficient, forecasts based on this heuristic are often too moderate (underestimation) with respect to both positive and negative changes (Slovic and Lichtenstein, 1971; Kahneman and Tversky, 1973).

These biases can be analyzed using traditional efficiency tests that evaluate whether forecast errors are orthogonal to the forecasts themselves as well as to prior forecast errors (Mincer and Zarnowitz, 1969; Nordhaus, 1987; Holden and Peel, 1990). These "behavioral" sources of forecast errors are captured in this study with three variables:[4] lagged forecast errors (e_{t-1}^{j} is the previous year's error for the same report month), percent change in forecast level (f_t^{j}), as described in equations (1) and (2), and percent change in forecast level multiplied by a negative change indicator (I=1 if $f_t^{j} < 0$, 0 otherwise). If forecasts are efficient, there should be no relationship between forecast errors and these variables; i.e., the null hypothesis is all coefficients are zero. Correlation with past errors indicates a systematic component in forecast errors that can be predicted using lagged errors, i.e. tendency to repeat or over-correct past errors. Anchoring would result in forecasters repeating previous errors while representativeness would lead to overcorrection of errors. Positive correlation with forecast level indicates that the absolute value of the forecast is smaller than the actual realization, underestimation of change in either direction, indicative of anchoring. Negative correlation means the change is overestimated, suggesting representativeness in predictions. When interacted with the negative change indicator, this variable describes the differences in forecasting positive versus negative change.

The second source of errors reflects data that are not (efficiently) incorporated in the forecasts. These could be uncovered through standard rationality and encompassing tests.

[4] Alternative specifications also included linear time trend to test for forecast improvement over time and dummy variables for changes in forecasting personnel. These variables were dropped from the final estimation due to high correlation with policy variables.

Diebold and Lopez (1998) identify the key property of optimal forecasts: "unforecastability [of the forecast errors] on the basis of information available at the time which the forecast was made." (p. 10). In our study we investigate whether USDA forecasts fail to efficiently take into account macroeconomic data and tend to show mistakes during certain economic conditions. Vogel and Bange (1999) note that USDA forecasting process "may include information on such diverse factors as exchange rates, oil prices, the effects of domestic and foreign agricultural policy and economic growth" (p. 14). These "macroeconomic" sources of forecast errors are summarized in this study within six variables described in table 2. Exchange rates are measured in this study using the trade weighted exchange index (FX), which represents a weighted average of the foreign exchange value of the U.S. dollar against the currencies of a broad group[5] of major U.S. trading partners. A stronger dollar (as manifested by an increase in FX index) would cause a drop in exports thus affecting total use and price. Oil prices affect multiple levels of input costs, from fertilizer (often derived from petroleum products) to transportation. Higher input costs would lead to contraction in production, which in combination with higher transportation costs would put an upward pressure on prices, which may lead to lower consumption. Spot price of West Texas Intermediate (WTI) crude oil at Cushing, Oklahoma location is used to measure this effect. The impact of economic growth and business cycles on WASDE forecasts is measured by Industrial Production Index (IPI, 2007 base) following Ludvigson and Ng (2005). As increases in industrial production illustrate periods of economic expansion, we expect consumption to increase during these times putting an upward pressure on price. [6] Tweeten

[5] Broad currency index includes the Euro area, Canada, Japan, Mexico, China, United Kingdom, Taiwan, Korea, Singapore, Hong Kong, Malaysia, Brazil, Switzerland, Thailand, Philippines, Australia, Indonesia, India, Israel, Saudi Arabia, Russia, Sweden, Argentina, Venezuela, Chile and Colombia. For more information about trade-weighted indexes see http://www.federalreserve.gov/pubs/bulletin/2005/winter05_index.pdf.

[6] Alternative specifications also included short term interest rate, which was dropped from the final estimation due to the high correlation with industrial production variable.

(1980) argue that inflation has a greater effect on prices paid by farmers relative to the prices received by farmers, contributing to a cost-price squeeze. Producer Price Index for farm products (PPI, 1982 base) is used to measure the impact of inflation on WASDE forecast errors.

Main changes in agricultural policy are reflected in the U.S. “Farm Bill” legislations. During the period of study, farm bills were enacted in 1990, 1996, 2002, and 2008. The largest changes were introduced in the 1996 Federal Agricultural Improvement and Reform (FAIR) Act, which introduced payments decoupled from production to insure compliance with WTO regulations. Decoupled farm payments were continued in somewhat different forms and levels in the subsequent 2002 and 2008 farm bills. The impact of changes in U.S. farm policy is modeled in this study using a Farm Bill dummy variable which equals 1 during 1986-1996 period and 0 otherwise. Other important pieces of legislation that had an impact on the U.S. grain and oilseed sectors are the 2005 Energy Policy and Renewable Fuel Act (RFA) and 2007 Energy Independence and Security Act (EISA). These legislations increased the amount of biofuel (usually ethanol) that must be mixed with gasoline sold in the U.S. from 2005 to 2012 thus increasing demand for ethanol and biofuel. Since the amount of biofuel in gasoline is mandated at an increasing rate, the impact of this legislation is modeled using a linear trend variable (RFA) for 2005-2010. RFA is expected to increase production, domestic use and the price of corn, as the new source of demand was introduced. Soybeans and wheat may experience a decline in production since more land is used for corn, thus resulting in higher prices as well. Our analysis will reveal whether USDA forecasters efficiently incorporated information about these macroeconomic factors in their estimates.

The third source of forecasting errors may stem from the data forecasters use. A recent Wall Street Journal article (Pleven, 2012) discusses the errors in pecan exports forecasts allegedly caused by data processing issues. Given the fact that all forecasts within a balance sheet are inter-related (as described in the data section), the errors in individual categories like exports would cause errors in aggregate categories, such as ending stocks and price. Due to the residual nature of ending stocks (total supply less total use), errors in ending stocks forecasts can be tracked down to their sources by regressing ending stocks forecast errors against the errors in all supply and use categories. [7]

Most fundamental models of commodity prices (Meyer, 1998; Westcott and Hoffman, 1999; Goodwin, Schnepf and Dohlman, 2005; Isengildina and MacDonald, 2009) rely on uncertain estimates of independent variables, thus errors in those variables would cause errors in price forecasts. Traditionally, in forecasting models price is specified as a function of the (ending) stocks-to-(total) use ratio. Thus, the U.S. balance sheet variables would affect the price forecasts through errors in ending stocks and total use. Given the global nature of the markets for commodities included in this study, we hypothesize that errors in U.S. prices for a commodity might also be affected by errors in its world ending stocks and total use. These variables were shown to be significant determinants of cotton prices in Isengildina and MacDonald (2009). Zero correlation between price forecast errors and errors in U.S. and world ending stocks and total use would indicate that price forecasts efficiently incorporate this information.

Estimation Method

All relevant[8] independent variables discussed above are included in the analysis of errors of all U.S. corn, soybean and wheat forecasts over 1987/88 through 2009/10 marketing years.

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[7] To avoid matrix singularity, imports for wheat and beginning stocks for all commodities were not included in these regressions.

[8] "Data" related sources of forecast error were only included in the analysis of price and ending stocks forecast errors.

Dependent variables are the absolute forecast errors, representing the size of error, and the forecast errors showing the forecast bias. For each crop and balance sheet item the following regressions were estimated:

$$(4)\ |e_t^j| = \alpha + \beta_l \sum_{l=1}^{3} S_l + \gamma|e_{t-1}^j| + \delta_1 f_t^j + \delta_2 f_t^j I_t + \theta_1 PPI_t^j + \theta_2 IPI_t^j + \theta_3 Oil_t^j + \theta_4 FX_t^j + \lambda_1 FB_t + \lambda_2 RFA_t + \phi_z \sum_{z=1}^{n} |e_t^{j,z}| + u_t^j,$$

and

$$(5)\ e_t^j = \alpha + \beta_l \sum_{l=1}^{3} S_l + \gamma e_{t-1}^j + \delta_1 f_t^j + \delta_2 f_t^j I_t + \theta_1 PPI_t^j + \theta_2 IPI_t^j + \theta_3 Oil_t^j + \theta_4 FX_t^j + \lambda_1 FB_t + \lambda_2 RFA_t + \phi_z \sum_{z=1}^{n} e_t^{j,z} + u_t^j,$$

where S_l are the forecasting cycle stages as defined in the WASDE forecasts section, e_{t-1}^j is the previous year's error for the same report month, f_t^j is percent change in forecast level, as described in equations (1) and (2), I_t is a negative change indicator ($I_t = 1$ if $f_t^j < 0$, 0 otherwise). PPI_t^j (producer price index), IPI_t^j (industrial production index), Oil_t^j (monthly average cash oil price), and FX_t^j (exchange rate index) are percent changes in macroeconomic variables and their calculations are explained later (equation 10). FB_t and RFA_t are agricultural policy variables described in table 2. The set $e_t^{j,z}$ includes data-driven sources of forecast errors associated with aggregate categories, ending stocks and price, and equals zero for all other categories. The set $e_t^{j,z}$ includes production, feed and residual, FSI, and export forecast errors for corn ending stocks equation; production, seed and residual, crushings, and export forecast errors for soybean ending stocks equation; and production, feed and residual, food, seed and export forecast errors for wheat ending stocks equation. On the other hand, the $e_t^{j,z}$ set includes U.S. total use, U.S. ending stocks, world total use and world ending stocks for all price equations.

All equations were estimated using ordinary least squares (OLS) method. However, as shown by Beck and Katz (1995) the OLS standard errors of the estimated parameters are incorrect when the time-series cross-section data are characterized by having repeated observations on fixed units. In order to correct for the correlation among the forecast months in a given marketing year and the correlation between the observations on the same calendar day we estimate the variance-covariance matrix as in Karali and Thurman (2009). Specifically, for a given crop we first run OLS regressions for each balance sheet category and obtain residuals. For production forecast errors we only use the first 8 report months as they are completed early during the marketing year. The residuals from the regression of production forecast errors are correlated across report months due to the fact that each monthly report is forecasting the same terminal event. We compute variances of residuals for each report month as the sample mean of the squared residuals across all marketing years as:

(6) $\hat{\sigma}_j^2 = \frac{1}{T}\sum_{t=1}^{T}\left(r_t^j\right)^2$, $T = 23$; $j = 1, \ldots, 8$ for corn and soybeans; $j = 1, \ldots, 5$ for wheat,

where r_t^j is the residual of report month j in marketing year t. Then, covariances between two report months are computed as the sample mean of the products of related residuals:

(7) $\hat{\sigma}_{ji} = \frac{1}{T}\sum_{t=1}^{T} r_t^j\, r_t^i$, $T = 23$; $j \neq i$; $j, i = 1, \ldots, 8$ for corn and soybeans; $j, i = 1, \ldots, 5$ for wheat.

For all other balance sheet categories, the correlation structure is more complicated. This is because of the overlapping forecasts released in the same report month. These forecasts are released on the same calendar day but correspond to two different marketing years since the forecasting cycle is longer than 12 months. However, because the information available is the same when these forecasts are made, these observations would be correlated. Thus, in addition to correlation between report months for a given marketing year, there also exists correlation between the forecasts of two consecutive marketing years that are released on the same calendar day. For instance, the 13th forecast figures for the marketing year 1987/1988 are released in May 1988. In the same WASDE report, the first forecast figures for the marketing year 1988/1989 are also released. Thus, the forecast errors of report months 13 through 18 (16) for marketing year *t* overlap with the forecast errors of report months 1 through 6 (4) for marketing year *t*+1 for corn and soybeans (wheat). Hence there are 6 (4) overlapping forecast errors in a marketing year for corn and soybeans (wheat), resulting in a total of 132 (88) overlapping observations.[9] To correct for this contemporaneous correlation we compute the covariance between the same-day observations as:

(8) $\hat{\sigma}_{t,t+1}^{j+12,j} = \frac{1}{n}\sum_{t=1}^{T-1} r_t^{j+12} r_{t+1}^{j}$, $T = 23$; $n = 132$; $j = 1, \dots, 6$ for corn and soybeans; $n = 88$; $j = 1, \dots, 4$ for wheat.

Variances of the residuals for each report month and covariances between the residuals of two report months in a given marketing year are computed as before:

(9)

$\hat{\sigma}_j^2 = \frac{1}{T}\sum_{t=1}^{T}\left(r_t^j\right)^2$, $\hat{\sigma}_{ji} = \frac{1}{T}\sum_{t=1}^{T} r_t^j\, r_t^i$, $T = 23$; $j \neq i$; $j, i = 1, \dots, 18$ for corn and soybeans;

$j, i = 1, \dots, 16$ for wheat.

Using these estimates we construct variance-covariance matrix of OLS residuals, and use it to compute standard errors of OLS parameter estimates. We present *t*-statistics computed using these standard errors along with OLS coefficient estimates in our result tables.

Results

Results of forecast evaluation for each category within WASDE corn, soybean and wheat balance sheets are shown in tables 3-5. For all balance sheet categories, coefficients of stage 1,

[9] Because T=23 forecast errors in that marketing year do not overlap with the forecast errors in the next marketing year. Thus, we have a total of 22x6=132 overlapping observations for corn and soybeans, and 22x4=88 for wheat.

2, and 3 variables in absolute percent error (APE) regressions illustrate reduction in the size of forecast error across the forecasting cycle as more information becomes available. Thus, stage 1 corn production forecast errors are on average 3.4% larger than stage 3 errors (errors in all other categories are interpreted relative to stage 4 errors). The largest reduction in the size of error is detected in corn exports forecasts, soybean seed and residual and ending stocks forecasts, and wheat feed and residual, exports, and ending stocks forecasts. Stage coefficients in the percent error regressions (PE) are interpreted as changes in bias across the forecasting cycle and can be compared to the average bias reported in table 1. For example, while table 1 reports average bias for soybean price as 2.12%, table 4 indicates that underestimation of soybean price is 4.66% larger in stage 1 forecasts and 2.99% larger in stage 2 forecasts relative to stage 4 forecasts. Underestimation in soybean crushings appears most pronounced in stage 2 and 3 forecasts, while overestimation of soybean ending stocks is prevalent in stages 1 and 2. Underestimation in stage 2 and 3 soybean export forecasts is offset with negative errors in other stages of the forecasting cycle as these forecasts are not biased on average according to table 1. According to table 5, bias in wheat forecasts is most prevalent in stage 2 for seed, and feed and residual and stage 1 for exports.

Behavioral Sources of Error

Absolute percent error regression results shown in table 3 indicate that the magnitude of errors in corn production and price forecasts was positively correlated with the size of previous forecast errors, revealing a pattern of large errors being followed by large errors. The magnitude of production forecast error decreases by 0.13% when corn production is forecasted to increase and increases by -0.13+0.23=0.10% with each percent decrease in forecasted production. Similar pattern is observed in feed and residual and price forecasts. On the other hand, the magnitudes of FSI and export forecast errors increase by 0.14% and 0.11% for positive changes and decrease by 0.18% and 0.015% for negative changes, respectively. The percent error regression results suggest that USDA corn market analysts have a tendency to overcorrect previous year's errors as suggested by the negative correlation with past errors in production, ending stocks, and feed and residual forecasts. Thus, a 10% overestimation of crop production in year *t* is followed by a 3% underestimation in year *t*+1. USDA analysts underestimate growth in corn production by 0.16% and overestimate contraction by the same amount. These tendencies are indicative of overreaction in year- to year corrections and pessimism. The bias is the opposite in FSI use forecasts, where tendency to repeat past errors and overestimate positive change by 0.28% and underestimate negative change by 0.19% suggests under-correction and optimism.

Absolute percent error regression results for soybeans shown in table 4 reveal a pattern of large errors being followed by small errors in seed and residual and crushings forecasts. The magnitude of production forecast error increases by -0.04+0.17=0.13% with each percent decrease in forecasted production. On the other hand, the magnitudes of seed and residual and ending stocks forecast errors increase by 0.38% and 0.13% for positive changes and decrease by 0.18% and 0.10% for negative changes, respectively. Positive changes in exports and price are predicted slightly more accurately than negative ones. Percent error regression results suggest that USDA soybean market analysts have a tendency to overcorrect previous year's errors as suggested by the negative correlation with past errors in production, seed and residual, exports, and price forecasts. Thus, a 10% overestimation of soybean price in year *t* is followed by a 2.3% underestimation in year *t*+1, suggesting a tendency for overreaction in these forecasts. USDA analysts underestimate growth in soybean crushings by 0.21% and overestimate contraction by

0.13%, which is indicative of pessimism. A tendency to overestimate contraction in production and ending stocks and growth in seed and residual and price is also detected.

Absolute percent error regression results for wheat shown in table 5 reveal a pattern of large errors being followed by large errors in ending stocks and price forecasts. The magnitude of feed and residual forecast errors increases by 0.26% for positive changes and decreases by 0.11% for negative changes. Forecasts of positive changes in price and negative changes in endings stocks have smaller errors. Percent error regression results suggest that USDA wheat market analysts have a tendency to repeat previous year's errors as suggested by the positive correlation with past errors in production, seed, ending stocks, and price forecasts. Thus, a 10% underestimation of wheat price in year *t* is followed by a 3.2% underestimation in year *t*+1, suggesting a tendency for undercorrection of past errors. USDA analysts overestimate growth in wheat food use and feed and residual use by 0.33% and 0.23%, respectively.

Macroeconomic Sources of Error

Forecast rationality implies that all relevant information is incorporated in the forecasts, thus forecast errors should be unpredictable using the information available at the time the forecasts are made. Because commodity forecasts in this study are measured as percent changes in forecasted values from the previous year's values (equations 1-2), macroeconomic variables are measured as percent changes from the previous year as well using:

(10) $M_t^j = 100 * ln\left(\frac{X_t^{j-1}}{X_{t-1}^{j-1+12}}\right), t = 1, \ldots, 23; j = 1, \ldots, J,$

where X_t^{j-1} is the value of the macro variable in WASDE forecast month *j*-1 for marketing year *t* and *J*=19 (17) for corn and soybeans (wheat). Similarly, X_{t-1}^{j-1+12} represents the value of that macro variable for the same calendar month but in the previous year. Because macro variables for the forecast month *j* are not known when those forecasts are made, the values of the macro variables from the previous forecast month, *j*-1, are used. If USDA forecasts efficiently incorporate macroeconomic information, percent error regression coefficients should be zero.

Analyses of corn forecast errors reported in table 3 demonstrate that 1% growth in inflation (PPI) causes 0.06% larger errors in corn feed and residual, 0.07% larger errors in price, and 0.20% underestimation in ending stocks forecasts. Economic growth (as evidenced by increase in IPI) leads to 0.24% larger errors in corn production, 0.18% larger errors associated with 0.17% overestimation in feed and residual, and 0.41% larger errors in exports forecasts. Information about oil price changes is not efficiently incorporated in all but export and price forecasts. Production, feed and residual and FSI forecast errors tend to grow by 0.05%, 0.02% along with 0.05% overestimation, and 0.01%, respectively, when oil prices decline. In contrast, ending stocks errors are positively correlated with oil price changes. Higher oil prices are associated with 0.05% overestimation of corn price. Information about exchange rate changes is not efficiently incorporated in all but feed and residual and ending stocks forecasts. Production, FSI, and price forecast errors tend to grow by 0.2%, 0.12%, and 0.14% associated with 0.39% underestimation, respectively, when U.S. dollar weakens against other currencies (decline in FX). Export forecast errors grow by 0.34% and feed and residual forecast errors show a tendency for underestimation when dollar strengthens. The Farm Bill variable describes the difference in the magnitude and direction of errors between the Farm Bill period of 1986-1996 and the post-1996 period. Production and feed and residual forecast errors are 5.18% and 1.46% larger and associated with 4.9% and 1.3% overestimation, respectively during the Farm Bill period, while FSI errors are 0.76% larger but do not show signs of bias. Tendency to underestimate corn exports during the Farm Bill period is also detected. RFA variable illustrates (annual) changes in errors during the 2005-2010 period. We observe a 0.38% decrease in FSI errors, 0.52% increase in price errors and underestimation in exports and ending stocks increasing by about 1.57% a year. It appears that feed and residual category is the most sensitive to changes in macro variables, and oil price and exchange rates are the factors causing most of the cases of inefficiency in corn forecasts.

Table 4 demonstrates that with higher inflation absolute percent errors of soybean seed and residual use and price forecasts grow by 0.24% and 0.12%, respectively, and a tendency for overestimation by 0.13% and 0.76% is observed in production and seed and residual forecasts, respectively. Ending stocks errors grow 1.01% during the periods of economic contraction (lower IPI), which are also associated with 1.66% overestimation of seed and residual and 0.52% underestimation of exports. Changes in oil prices are not efficiently incorporated in seed and residual, ending stocks, and price forecasts. Lower oil prices leads to 0.08% larger errors in seed and residual and 0.05% larger errors associated with 0.05% underestimation in price forecasts. Higher oil prices cause 0.16% larger errors in ending stocks, and underestimation in production forecasts by 0.03% and in exports forecasts by 0.06%. Weaker dollar (lower FX) leads to 0.3% larger errors in production and 0.4% larger errors associated with 0.5% underestimation in price forecasts. Stronger dollar is associated with underestimation in seed and residual (0.73%) and crushings (0.14%) forecasts. Errors of production forecasts are 1.12% larger and have a tendency of underestimation (2.82%) during the Farm Bill period, which is also characterized by 1.59% larger exports forecast errors and 4.87% smaller seed and residual errors. Seed and residual forecast errors grow (by 1.6% a year) while ending stocks forecast errors decline (by 1.7% a year) during the RFA period. A growing tendency to underestimate production (by 0.65% a year) is also detected during the RFA period. Overall, seed and residual is the most affected category by macroeconomic factors, and the oil price is the biggest source of inefficiency in WASDE soybean forecasts.

Table 5 shows that higher inflation leads to 0.98% larger errors associated with 1.75% overestimation in wheat feed and residual forecasts as well as a tendency for 0.10% underestimation in price forecasts. Errors of seed and feed and residual and underestimation in price forecasts increase during the periods of economic growth. Lower oil price has a relatively mild effect on wheat forecasts by increasing the errors of production (0.08%) and seed (0.02%) use categories only. Exchange rates have the most profound impact on all categories except price. Weaker dollar leads to 0.51% larger errors in production, 0.06% larger errors associated with 0.12% overestimation in food use, 1.01% larger errors associated with 1.30% overestimation in feed and residual use, and 0.24% larger errors in exports forecasts. Stronger dollar causes 0.11% larger errors associated with 0.19% overestimation in seed use forecasts and a tendency for underestimation (0.41%) in ending stocks. The Farm Bill period is characterized by 0.77% larger errors in food forecasts, 6.95% smaller errors in production, and 2.40% smaller errors associated with 4.55% underestimation in seed use forecasts as well as a tendency for underestimation (5.01%) in exports. Errors in production, food, and seed forecasts decrease while errors in feed and residual and price forecasts increase during the RFA period. An increasing tendency for underestimation is detected in food (by 0.35% a year), seed (by 0.88% a year) and ending stocks (by 1.60% a year) forecasts, while feed and residual use is increasingly overestimated (by 4.99% a year) during the RFA period. It appears that feed and residual category is the most affected by macroeconomic factors and the exchange rate is the biggest source of inefficiency in WASDE wheat forecasts.

Data-related Sources of Error

Results presented in table 6 demonstrate that the size of corn ending stocks forecast errors is most sensitive to the size of errors in FSI and production forecasts. In terms of bias, as expected, ending stock errors were positively correlated with production forecast errors and negatively correlated with use (domestic and exports). Thus, a 1% underestimation of corn production causes a 4.44% underestimation in ending stocks. A 1% underestimation in feed and residual use results in 2.5% overestimation in ending stocks. On the other hand, errors in FSI and exports are transmitted in ending stocks errors about the same proportion. For soybean ending stocks, the size of error is most sensitive to the size of errors in production and crushings forecasts, which are also the main sources of bias. A 1% underestimation in soybean production causes a 7.22% underestimation in ending stocks, underestimation in crushings causes a 3.7% overestimation, and underestimation in exports leads to 2.6% overestimation in ending stocks, while underestimation in seed and residual results in a much smaller impact on ending stock errors. For wheat ending stocks, the size of error is most sensitive to the size of errors in production and seed forecasts. A 1% underestimation in wheat production causes a 2.13% underestimation in ending stocks, while underestimation in exports causes a 1.4% overestimation in ending stocks. The impact of other variables (food, seed, and feed and residual use), while significantly different from zero, is of a much smaller magnitude.

Our results for data-related sources of errors in price forecasts demonstrate that U.S. ending stocks forecasts are the main source of price forecast errors across all three commodities. The impact is the largest in wheat, where a 1% increase in ending stocks absolute percent error leads to a 0.48% increase in price error. In terms of bias, the relationship is negative, thus a 1% underestimation in wheat ending stocks, results in 0.52% overestimation in price. Wheat price errors are also correlated with the size and the direction of U.S. total use forecasts. When total use is underestimated by 1%, price is overestimated by 0.62%. Similar correlation, of a slightly smaller magnitude is observed in soybeans. World stocks and use variables do not have much impact on prices with only a small (0.07%) correlation detected between the size of world ending stocks and corn price errors.

Summary and Conclusions

This study sought to examine USDA corn soybean and wheat forecast errors from 1987/88 through 2009/10 marketing years to better understand when forecasters make mistakes. We hypothesized that errors may stem from three general sources: behavioral, macroeconomic, and data-related. Rationality-type tests were used to examine whether information related to the above sources available at the time the forecasts are made can be used to predict forecast errors.

Our findings demonstrate that corn and soybean forecasters tend to overcorrect previous mistakes. For example, a 1% overestimation in corn production in the previous year is likely to be followed by a 0.3% underestimation in current year. On the other hand, wheat forecasters tend to repeat their previous errors. Thus a 1% overestimation in wheat production in the previous year is likely to be followed by a 0.2% overestimation in current year. Underestimation of growth and overestimation of contraction consistent with conservativeness (pessimism) heuristic is observed in corn production and soybean production, crushings, and ending stocks. Overestimation of growth and/or underestimation of contraction consistent with leniency (optimism) are observed in corn FSI, soybean seed and residual and price, and wheat food and feed and residual.

Not all of the macroeconomic factors included in this study (exchange rates, oil prices, economic growth, inflation, and policy variables) are found to be efficiently incorporated in WASDE forecasts. Exchange rate and oil price-related inefficiencies are the most widespread. USDA forecasters appear to overestimate corn and soybean price and underestimate use (corn feed and residual and soybean exports) as well as supply (soybean production) during the periods of increasing oil prices. Appreciation of U.S. exchange rate is associated with overestimation of corn and soybean price, underestimation of some domestic use categories (corn feed and residual, soybean crushings, and seed and residual, wheat food and feed and residual), underestimation in wheat ending stocks, and overestimation in wheat exports and seed use. Higher inflation is associated with underestimation of corn ending stocks and wheat price, overestimation of wheat feed and residual use, as well as overestimation of soybean production and seed and residual use. Increasing tendencies for underestimation of corn exports and ending stocks, soybean production and wheat food, seed and ending stocks are detected during the RFA period (2005-2010), while wheat feed and residual use is increasingly overestimated during this time.

Analyses of data-related sources of error reveal that errors in ending stocks forecasts are mostly driven by errors in production forecasts across all commodities. Among use categories, corn feed and residual, soybean crushing, and wheat export errors have the biggest impact on endings stocks errors. Errors in price forecasts are caused by errors in U.S. ending stocks forecasts for all commodities and total use forecasts for soybeans and wheat.

Fildes and Stekle (2002) argue that “The use of rationality tests, especially those that relate the forecast errors to known information, can … be viewed as important diagnostic checks to determine why the errors occurred and to improve the forecasting process and the quality of subsequent predictions" (p. 454). Our findings can thus be used to improve USDA forecasts.

The findings of this study can also be used by market participants to help interpret USDA information. If market participants are fully aware of the flaws and inefficiencies in USDA forecasts and adjust for them in their decision making process, limited or no economic losses would result (Orazem and Falk, 1989). The degree to which market participants anticipate and adjust information contained in USDA forecasts is outside the scope of this study and presents an interesting area for future research.

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Table 1. Descriptive Statistics of WASDE Forecasts for U.S. Corn, Soybeans and Wheat, 1987/88 -2009/10 Marketing Years.

Forecast Variable	Mean (y)	Standard Dev. (y)	CV (y)	Mean (f)	Standard Dev. (f)	MAPE ($\lvert e \rvert$)	MPE (e)	Bias (t-test)
						-----%	------	
Corn								
Production	9536	2120	0.222	1.712	21.247	1.738	-0.227	-0.644
Food, Seed, Industrial	2493	1488	0.597	0.066	9.042	1.790	-0.121	-0.364
Feed and Residual	5311	579	0.109	7.024	6.107	2.757	-0.075	-0.855
Exports	1900	269	0.141	0.829	18.889	6.901	0.212	0.413
Ending Stocks	1578	718	0.455	-6.105	51.616	14.246	0.986	0.885
Price	2.63	0.85	0.324	5.164	19.557	5.161	1.093	2.585 **
Soybeans								
Production	2546	510	0.200	2.250	12.997	2.055	0.249	0.901
Crushings	1497	229	0.153	1.395	5.720	1.995	0.718	5.442 ***
Seed and Residual	131	37	0.280	2.852	16.921	14.456	-1.661	5.189 ***
Exports	932	262	0.282	0.930	24.908	5.659	2.073	-1.628
Ending Stocks	252	105	0.417	-2.946	44.575	21.331	-8.764	-6.421 ***
Price	6.62	1.86	0.282	3.567	18.227	4.383	2.121	5.580 ***
Wheat								
Production	2205	262	0.119	0.225	16.042	2.342	-0.365	-0.647
Food	876	72	0.083	1.025	2.761	1.696	-0.029	-0.230
Seed	87	10	0.115	-0.701	9.122	3.631	-1.846	-6.670 ***
Feed and Residual	228	103	0.451	-4.460	71.105	23.567	-12.079	-5.515 ***
Exports	1135	180	0.158	1.041	18.912	5.692	1.265	2.651 ***
Ending Stocks	664	231	0.348	-3.116	34.885	12.091	0.112	0.117
Price	3.76	1.19	0.315	3.570	19.733	5.766	2.021	3.217 ***

Notes: y is forecast level measured in million bushels and $/bushel. f is a % change in the forecast from the previous year's forecast. Means and standard deviations of forecast level (y) and forecast change (f) are computed using the final estimates (j=19) only. Mean absolute percent error (MAPE) and mean percent error (MPE) are computed for j=1, ..., 18. One asterisk (*) indicates significance at the 10% level, two asterisks (**) indicate significance at the 5% level, and three asterisks (***) indicate significance at the 1% level.

Table 2. Description and Summary Statistics for Macroeconomic Sources of Forecast Errors, 1987/88 -2009/10 Marketing Years.

Variable Name	Description	Mean	Std. Dev.
FX	Trade Weighted Exchange Index (Broad), 1997 base year	2.271	5.915
Oil Price	WTI FOB spot price	6.385	30.605
IPI	Industrial Production Index, 2007 base year	2.042	4.054
PPI	Producer Price Index for commodities (farm products) 1982 base year;	1.747	10.572
Farm Bill	1 for 1986-1996, 0 otherwise	0.411	0.493
RFA	linear trend for 2005-2010	0.797	1.622

Table 3. Analysis of Behavioral and Macro Driven Errors in Corn Forecasts, 1987/88 -2009/10 Marketing Years.

Dependent Variable	Absolute Percent Error (APE)						Percent Error (PE)					
Independent Variables	Production	Feed & Residual	Food, Seed, Industrial	Exports	Ending Stocks	Average Price	Production	Feed & Residual	Food, Seed, Industrial	Exports	Ending Stocks	Average Price
Intercept	0.681	0.125	-0.345	-1.227	1.325	0.073	-0.499	0.411	2.525 ***	-4.440 *	-0.558	-0.344
	(0.61)	(0.28)	(-0.81)	(-0.92)	(0.48)	(0.08)	(-0.34)	(0.55)	(4.28)	(-1.71)	(-0.27)	(-0.24)
Stage 1 (May-Aug)	3.393 ***	4.302 ***	2.807 ***	12.594 ***	5.144	5.531 ***	-0.851	0.886	-0.178	0.235	3.627	2.470
	(3.55)	(6.95)	(6.54)	(9.53)	(1.51)	(4.46)	(-0.63)	(1.02)	(-0.32)	(0.10)	(1.57)	(1.58)
Stage 2 (Sep-Nov)	1.073	2.869 ***	2.491 ***	10.606 ***	4.784 **	2.943 ***	0.762	0.687	-0.055	0.046	1.421	2.295
	(1.03)	(5.73)	(6.18)	(8.90)	(1.75)	(3.16)	(0.63)	(0.83)	(-0.13)	(0.02)	(0.80)	(1.65)
Stage 3 (Dec-Aug)		1.275 ***	1.051 ***	3.725 ***	2.755 **	0.241		-0.638 *	-0.273	0.667	1.708	0.877
		(5.03)	(4.14)	(5.72)	(1.86)	(0.43)		(-1.71)	(-0.94)	(0.57)	(1.27)	(0.98)
Lagged (A)PE	0.202 ***	0.008	0.014	0.034	0.017	0.124 **	-0.290 ***	-0.234 ***	0.154 *	-0.107	-0.069 *	0.020
	(2.81)	(0.12)	(0.16)	(0.52)	(0.33)	(2.31)	(-3.13)	(-3.47)	(1.72)	(-1.24)	(-1.73)	(0.34)
Forecast (*f*)	-0.129 ***	-0.106 *	0.137 ***	0.111 *	-0.057	-0.073 *	0.163 ***	0.026	-0.279 ***	0.033	-0.034	0.041
	(-3.03)	(-1.77)	(2.96)	(1.69)	(-1.15)	(-1.92)	(2.86)	(0.28)	(-4.28)	(0.26)	(-0.92)	(0.70)
Negative Forecast	0.229 ***	0.191 **	-0.319 *	-0.126	-0.009	0.163 *	-0.326 ***	0.004	0.471 *	0.024	0.033	-0.083
	(2.96)	(2.05)	(-1.68)	(-1.11)	(-0.12)	(1.98)	(-2.94)	(0.03)	(1.89)	(0.11)	(0.58)	(-0.69)
PPI	0.058	0.059 ***	0.000	0.001	0.174	0.073 *	-0.017	0.014	0.001	-0.030	0.199 **	0.012
	(1.53)	(2.85)	(-0.02)	(0.01)	(1.47)	(1.92)	(-0.25)	(0.46)	(0.02)	(-0.31)	(2.13)	(0.17)
IPI	0.236 *	0.184 ***	-0.045	0.414 ***	-0.281	0.163	-0.065	-0.169 *	-0.090	0.442	0.257	0.257
	(1.87)	(3.09)	(-1.02)	(2.91)	(-0.79)	(1.54)	(-0.33)	(-1.88)	(-1.48)	(1.56)	(1.00)	(1.55)
Oil Price	-0.051 ***	-0.022 ***	-0.011 *	-0.011	0.082 *	-0.002	0.019	0.047 ***	-0.003	-0.048	-0.006	-0.047 **
	(-3.03)	(-2.77)	(-1.92)	(-0.59)	(1.93)	(-0.14)	(0.80)	(3.99)	(-0.35)	(-1.30)	(-0.17)	(-2.27)
FX	-0.208 **	0.000	-0.122 ***	0.335 ***	0.225	-0.143 *	0.005	0.128 *	-0.067	-0.016	0.118	-0.387 ***
	(-2.22)	(0.01)	(-3.53)	(3.04)	(0.87)	(-1.86)	(0.03)	(1.89)	(-1.35)	(-0.08)	(0.60)	(-3.29)
Farm Bill	5.183 ***	1.455 ***	0.758 *	-1.687	-4.368	0.570	-4.896 ***	-1.273 *	-0.655	6.455 ***	-3.026	0.310
	(4.84)	(3.09)	(1.96)	(-1.48)	(-1.61)	(0.68)	(-2.92)	(-1.76)	(-1.20)	(2.74)	(-1.38)	(0.24)
RFA	-0.107	0.198	-0.379 **	-0.229	-0.178	0.524 *	-0.146	-0.212	0.162	1.572 **	1.567 **	0.307
	(-0.28)	(1.29)	(-2.51)	(-0.60)	(-0.20)	(1.83)	(-0.25)	(-0.92)	(0.80)	(2.07)	(2.40)	(0.77)
OLS R-sq	0.317	0.398	0.320	0.431	0.557	0.615	0.192	0.201	0.246	0.114	0.751	0.497
OLS Adj R-sq	0.269	0.379	0.298	0.413	0.538	0.599	0.136	0.175	0.222	0.085	0.741	0.475
N	184	414	414	414	414	414	184	414	414	414	414	414

Notes: Ending Stocks and Price regressions also include data driven sources of errors described in table 6. Absolute lagged errors were included in absolute percent error regressions and lagged errors were included in percent error regressions. Negative forecast is forecast (*f*) times a negative change indicator. Numbers in parentheses are t-statistics. One asterisk (*) indicates significance at the 10% level, two asterisks (**) indicate significance at the 5% level, and three asterisks (***) indicate significance at the 1% level.

Table 4. Analysis of Behavioral and Macro Driven Errors in Soybean Forecasts, 1987/88 -2009/10 Marketing Years.

Dependent Variable	Absolute Percent Error (APE)						Percent Error (PE)					
Independent Variables	**Production**	**Seed and Residual**	**Crushings**	**Exports**	**Ending Stocks**	**Average Price**	**Production**	**Seed and Residual**	**Crushings**	**Exports**	**Ending Stocks**	**Average Price**
Intercept	2.064 **	2.962	0.029	0.078	2.798	0.788	-2.643 **	-4.180	-1.183 *	-0.041	-4.735 **	0.931
	(2.13)	(1.02)	(0.07)	(0.08)	(1.04)	(0.72)	(-2.06)	(-1.41)	(-1.96)	(-0.03)	(-2.44)	(0.63)
Stage 1 (May-Aug)	3.990 ***	17.972 ***	3.868 ***	9.450 ***	21.385 ***	6.201 ***	-0.266	1.821	0.425	1.964	-11.131 ***	4.661 ***
	(4.78)	(4.35)	(10.82)	(7.62)	(4.75)	(4.01)	(-0.18)	(0.54)	(0.91)	(1.21)	(-5.16)	(2.99)
Stage 2 (Sep-Nov)	1.154	15.454 ***	3.100 ***	8.540 ***	18.437 ***	4.603 ***	0.599	0.159	1.349 ***	5.198 ***	-4.230 **	2.989 **
	(1.26)	(5.68)	(8.76)	(6.98)	(5.66)	(3.59)	(0.54)	(0.05)	(3.08)	(3.62)	(-2.50)	(2.19)
Stage 3 (Dec-Aug)		8.215 ***	1.712 ***	3.113 ***	9.287 ***	0.805		-1.519	1.234 ***	2.582 **	-1.783	1.039
		(3.99)	(8.34)	(4.70)	(4.76)	(1.02)		(-0.76)	(3.63)	(2.70)	(-1.26)	(1.01)
Lagged (A)PE	0.079	-0.252 ***	-0.150 ***	-0.028	-0.069	0.002	-0.174 *	-0.181 **	-0.034	-0.290 ***	-0.015	-0.228 ***
	(1.34)	(-2.85)	(-2.86)	(-0.40)	(-1.00)	(0.02)	(-1.75)	(-2.30)	(-0.49)	(-3.23)	(-0.47)	(-2.81)
Forecast (*f*)	-0.039	0.376 ***	0.034	-0.114 *	0.127 ***	-0.086 *	-0.015	-0.318 ***	0.213 **	-0.073	0.023	-0.110 *
	(-0.93)	(5.13)	(0.60)	(-2.00)	(3.21)	(-1.81)	(-0.26)	(-3.53)	(2.21)	(-0.72)	(0.64)	(-1.69)
Negative Forecast	0.171 **	-0.561 ***	-0.096	0.078	-0.233 ***	0.109	-0.218 *	-0.117	-0.340 **	0.107	-0.209 ***	0.108
	(2.21)	(-4.14)	(-1.13)	(0.87)	(-3.43)	(1.30)	(-1.86)	(-0.74)	(-2.27)	(0.70)	(-4.07)	(0.99)
PPI	0.001	0.235 **	0.009	-0.034	-0.072	0.122 **	-0.129 ***	-0.759 ***	0.008	0.023	-0.088	0.072
	(0.03)	(1.88)	(0.67)	(-0.80)	(-0.53)	(2.46)	(-3.00)	(-5.50)	(0.39)	(0.34)	(-1.04)	(1.04)
IPI	0.132	0.027	0.045	0.100	-1.013 ***	0.116	0.046	1.659 ***	0.085	-0.524 **	-0.125	0.259
	(1.45)	(0.08)	(1.15)	(0.84)	(-3.13)	(0.96)	(0.38)	(4.42)	(1.24)	(-2.69)	(-0.55)	(1.62)
Oil Price	-0.018	-0.082 *	0.002	0.018	0.164 ***	-0.048 ***	0.029 *	0.072	-0.004	0.056 **	0.044	-0.047 **
	(-1.46)	(-1.84)	(0.29)	(1.04)	(3.45)	(-3.02)	(1.72)	(1.37)	(-0.50)	(2.12)	(1.47)	(-2.27)
FX	-0.292 ***	0.037	0.023	-0.038	0.227	-0.390 ***	0.099	0.733 **	0.135 ***	-0.091	0.057	-0.490 ***
	(-4.28)	(0.15)	(0.79)	(-0.40)	(0.87)	(-4.27)	(1.07)	(2.53)	(2.86)	(-0.60)	(0.33)	(-4.04)
Farm Bill	1.117 *	-4.866 *	-0.394	1.589 *	-2.351	0.420	2.824 ***	-0.788	-0.008	2.646	2.648	2.115
	(1.71)	(-1.98)	(-1.36)	(1.69)	(-0.96)	(0.40)	(3.56)	(-0.24)	(-0.01)	(1.60)	(1.33)	(1.57)
RFA	-0.393	1.602 *	-0.118	0.385	-1.695 **	0.128	0.652 *	-1.524	-0.138	0.684	0.673	0.157
	(-1.40)	(1.76)	(-1.17)	(1.32)	(-2.20)	(0.40)	(1.92)	(-1.45)	(-0.78)	(1.35)	(1.05)	(0.38)
OLS R-sq	0.346	0.306	0.324	0.340	0.413	0.437	0.133	0.422	0.222	0.185	0.884	0.310
OLS Adj R-sq	0.300	0.284	0.302	0.318	0.388	0.413	0.073	0.403	0.196	0.158	0.879	0.280
N	184	414	414	414	414	414	184	414	414	414	414	414

Notes: Ending Stocks and Price regressions also include data driven sources of errors described in table 6. Absolute lagged errors were included in absolute percent error regressions and lagged errors were included in percent error regressions. Negative forecast is forecast (*f*) times a negative change indicator. Numbers in parentheses are t-statistics. One asterisk (*) indicates significance at the 10% level, two asterisks (**) indicate significance at the 5% level, and three asterisks (***) indicate significance at the 1% level.

Table 5. Analysis of Behavioral and Macro Driven Errors in Wheat Forecasts, 1987/88 -2009/10 Marketing Years.

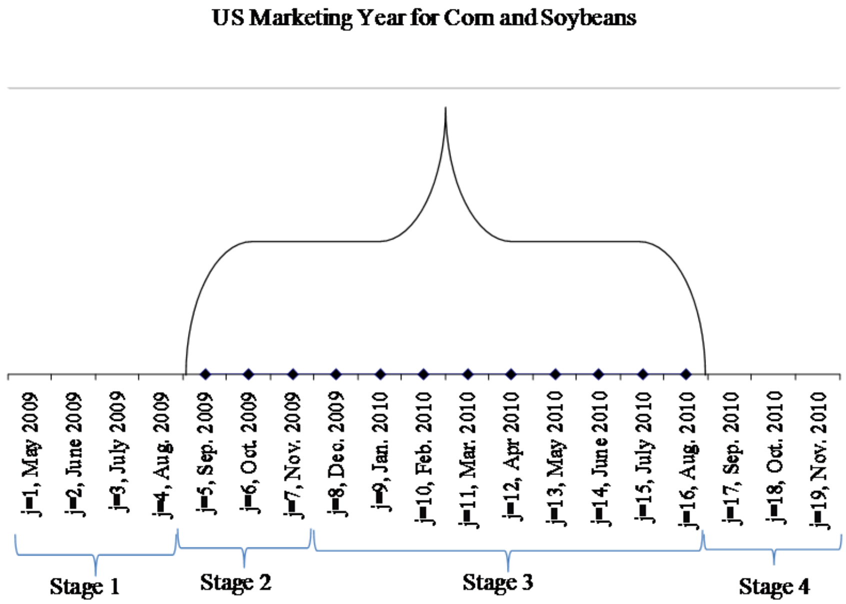
Dependent Variable	Absolute Percent Error (APE)							Percent Error (PE)						
Independent Variables	**Production**	**Food**	**Seed**	**Feed and Residual**	**Exports**	**Ending Stocks**	**Average Price**	**Production**	**Food**	**Seed**	**Feed and Residual**	**Exports**	**Ending Stocks**	**Average Price**
Intercept	8.447 ***	0.639	0.958	-6.912	0.906	-1.804	0.134	1.988	-0.293	-2.463 **	-0.259	-3.246	-5.194 **	-0.991
	(3.74)	(1.36)	(1.02)	(-0.94)	(0.58)	(-0.77)	(0.09)	(0.58)	(-0.39)	(-2.08)	(-0.03)	(-1.39)	(-2.49)	(-0.76)
Stage 1 (May-Jun)	7.621 ***	1.963 ***	6.332 ***	35.668 ***	12.089 ***	12.578 ***	8.488 ***	-0.622	0.153	-1.385	-9.759	4.168 **	0.544	2.426
	(4.41)	(3.95)	(5.75)	(4.77)	(8.47)	(3.70)	(3.85)	(-0.24)	(0.24)	(-1.26)	(-1.28)	(2.06)	(0.32)	(1.63)
Stage 2 (Jul-Aug)	5.933 ***	1.974 ***	6.443 ***	36.046	12.417 ***	10.837 ***	6.622 ***	-1.107	0.159	-2.633 **	-21.156 **	3.306	-0.920	1.993
	(4.37)	(4.48)	(6.04)	(4.60)	(7.98)	(3.38)	(3.10)	(-0.41)	(0.25)	(-2.16)	(-2.54)	(1.58)	(-0.50)	(1.37)
Stage 3 (Sep-May)		1.477 ***	2.597 ***	12.909 **	3.587 ***	3.376 **	-0.712		-0.079	-1.173	-7.981	0.802	1.019	1.073
		(4.58)	(4.08)	(2.04)	(4.11)	(2.06)	(-0.75)		(-0.15)	(-1.48)	(-1.21)	(0.68)	(0.93)	(1.20)
Lagged (A)PE	0.028	-0.102	0.009	0.083	0.019	0.134 **	0.099 *	0.220 *	0.064	0.187 **	0.042	0.094	0.231 ***	0.318 ***
	(0.27)	(-1.43)	(0.11)	(0.99)	(0.24)	(2.15)	(2.00)	(2.03)	(0.69)	(2.58)	(0.49)	(0.97)	(5.48)	(9.27)
Forecast (*f*)	-0.108	0.037	0.068	0.260 ***	-0.023	0.022	-0.061 *	-0.118	-0.335 **	-0.103	-0.230 **	0.098	-0.062	0.042
	(-1.34)	(0.49)	(1.09)	(2.85)	(-0.32)	(0.5)	(-1.96)	(-1.13)	(-2.59)	(-1.21)	(-2.17)	(0.89)	(-1.64)	(1.44)
Negative Forecast	0.264	0.090	-0.135	-0.375 **	-0.009	-0.107 *	0.058	0.282	0.228	0.021	0.077	-0.243	-0.079	-0.022
	(1.66)	(0.52)	(-1.20)	(-2.40)	(-0.08)	(-1.70)	(1.03)	(1.28)	(0.84)	(0.14)	(0.44)	(-1.33)	(-1.25)	(-0.42)
PPI	0.020	0.018	0.047	0.982 ***	-0.044	0.084	0.056	0.030	0.014	0.051	-1.747 ***	0.063	-0.090	0.103 **
	(0.31)	(1.26)	(1.52)	(3.94)	(-0.82)	(1.05)	(1.23)	(0.29)	(0.61)	(1.35)	(-5.97)	(0.75)	(-1.17)	(2.25)
IPI	0.268	-0.020	0.180 **	1.641 **	-0.021	-0.039	0.179	-0.123	0.027	-0.053	0.223	-0.124	0.371	0.241 *
	(1.10)	(-0.47)	(2.13)	(2.06)	(-0.13)	(-0.16)	(1.38)	(-0.35)	(0.38)	(-0.48)	(0.24)	(-0.50)	(1.56)	(1.80)
Oil Price	-0.082 ***	-0.008	-0.020 *	-0.139	0.021	0.000	-0.009	0.047	0.014	0.015	0.170	0.011	0.028	0.000
	(-2.83)	(-1.56)	(-1.77)	(-1.28)	(1.06)	(0.01)	(-0.56)	(1.21)	(1.59)	(1.06)	(1.39)	(0.37)	(1.02)	(-0.01)
FX	-0.507 ***	-0.059 *	0.112 *	-1.008 *	-0.237 **	0.241	-0.130	0.297	0.117 **	-0.190 **	1.299 **	-0.385 **	0.412 **	-0.017
	(-3.40)	(-1.93)	(1.84)	(-1.87)	(-2.10)	(1.41)	(-1.43)	(1.50)	(2.35)	(-2.41)	(2.10)	(-2.14)	(2.53)	(-0.18)
Farm Bill	-6.953 ***	0.766 **	-2.403 ***	0.719	1.144	0.410	-0.537	-2.097	0.556	4.551 ***	0.154	5.009 **	1.475	0.237
	(-4.51)	(2.35)	(-3.44)	(0.12)	(0.82)	(0.19)	(-0.49)	(-1.33)	(0.95)	(4.65)	(0.02)	(2.31)	(0.68)	(0.22)
RFA	-1.391 **	-0.267 **	-0.515 **	4.795 **	-0.581	-0.729	0.740 *	-0.527	0.348 *	0.883 ***	-4.989 *	0.568	1.604 **	0.229
	(-2.09)	(-2.30)	(-2.31)	(2.23)	(-1.32)	(-1.03)	(1.88)	(-0.61)	(1.73)	(2.82)	(-2.02)	(0.85)	(2.41)	(0.63)
OLS R-sq	0.501	0.286	0.369	0.384	0.449	0.449	0.736	0.102	0.156	0.325	0.370	0.190	0.820	0.833
OLS Adj R-sq	0.442	0.260	0.346	0.362	0.429	0.429	0.723	-0.004	0.125	0.300	0.347	0.160	0.811	0.825
N	115	368	368	368	368	368	368	115	368	368	368	368	368	368

Notes: Ending Stocks and Price regressions also include data driven sources of errors described in table 6. Absolute lagged errors were included in absolute percent error regressions and lagged errors were included in percent error regressions. Negative forecast is forecast (f) times a negative change indicator. Numbers in parentheses are t-statistics. One asterisk (*) indicates significance at the 10% level, two asterisks (**) indicate significance at the 5% level, and three asterisks (***) indicate significance at the 1% level.

Table 6. Analysis of Data Driven Errors in WASDE Corn, Soybean and Wheat Forecasts, 1987/88 -2009/10 Marketing Years

Dependent Variable	Absolute Percent Error (APE)			Percent Error (PE)		
Independent Variables	**Corn**	**Soybean**	**Wheat**	**Corn**	**Soybean**	**Wheat**
			Ending Stocks			
Production (A)PE	1.560 ***	1.499 ***	0.368 **	4.437 ***	7.222 ***	2.128 ***
	(6.16)	(3.12)	(2.04)	(21.44)	(20.40)	(13.58)
Feed and Res. (A)PE	0.614		0.107 ***	-2.509 ***		-0.094 ***
	(1.43)		(4.50)	(-8.83)		(-3.78)
Seed and Res. (A)PE		0.038			-0.196 ***	
		(0.45)			(-4.19)	
FSI (A)PE	2.093 ***			-1.330 ***		
	(4.42)			(-3.93)		
Crushings (A)PE		1.883 **			-3.685 ***	
		(2.39)			(-7.86)	
Food (A)PE			-0.337			-0.836 **
			(-0.69)			(-2.40)
Exports (A)PE	0.266 *	-0.352	0.059	-1.121 ***	-2.570 ***	-1.375 ***
	(1.80)	(-1.34)	(0.45)	(-11.38)	(-18.96)	(-11.81)
Seed (A)PE			0.572 ***			-0.353 **
			(2.80)			(-2.09)
			Price			
US Total Use (A)PE	-0.054	0.028	-0.521 ***	-0.094	-0.431 **	-0.625 ***
	(-0.33)	(0.16)	(-3.77)	(-0.34)	(-2.28)	(-6.45)
US Ending Stocks (A)PE	0.136 ***	0.096 ***	0.484 ***	-0.244 ***	-0.092 ***	-0.517 ***
	(6.52)	(3.98)	(13.99)	(-6.95)	(-3.55)	(-20.40)
World Total Use (A)PE	0.353	0.018	-0.427	0.402	-0.172	-0.208
	(0.96)	(0.07)	(-1.32)	(0.70)	(-0.63)	(-0.83)
World Ending Stocks (A)PE	0.071 *	0.013	0.032	-0.032	-0.019	0.001
	(1.67)	(0.23)	(0.61)	(-0.49)	(-0.32)	(0.02)

Notes: Absolute errors were included in the absolute error regressions and percent errors were included in percent error regressions.



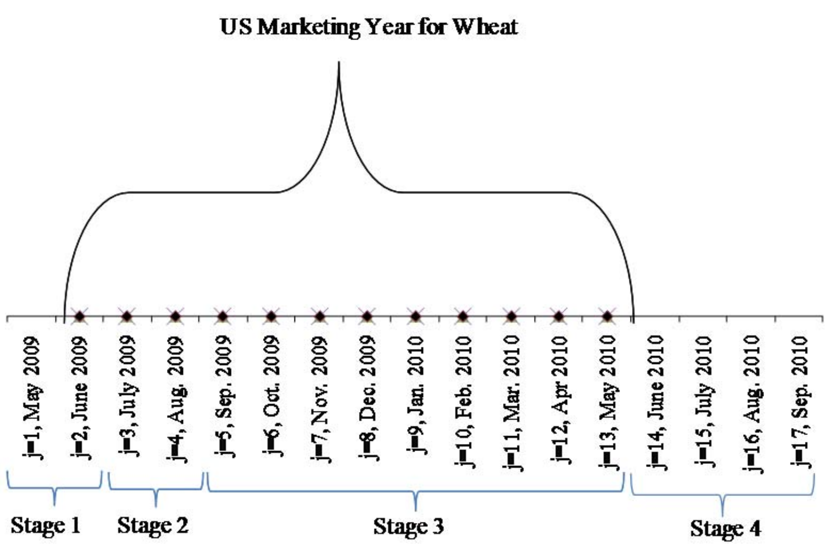


Figure 1. The 2009/2010 WASDE forecasting cycle for corn, soybeans and wheat relative to the U.S. marketing year